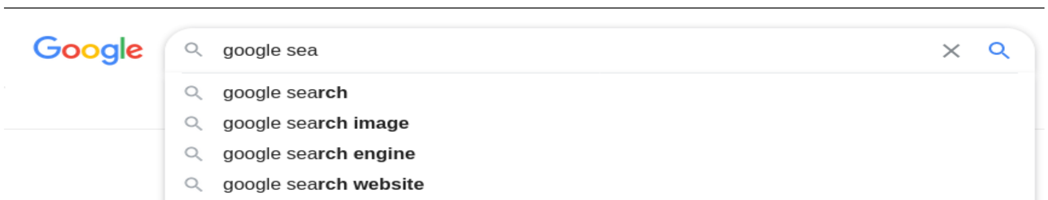
MACHINE LEARNING

1.1.1. Examples of ML in Everyday Life

While ChatGPT is a particularly prominent example of a system powered by machine learning, there exist many other ways in which machine learning is deployed around us. In fact, you may have interacted with ML-based systems today without even realizing it. Let's look at a few examples and gradually work our way towards a precise definition of machine learning.

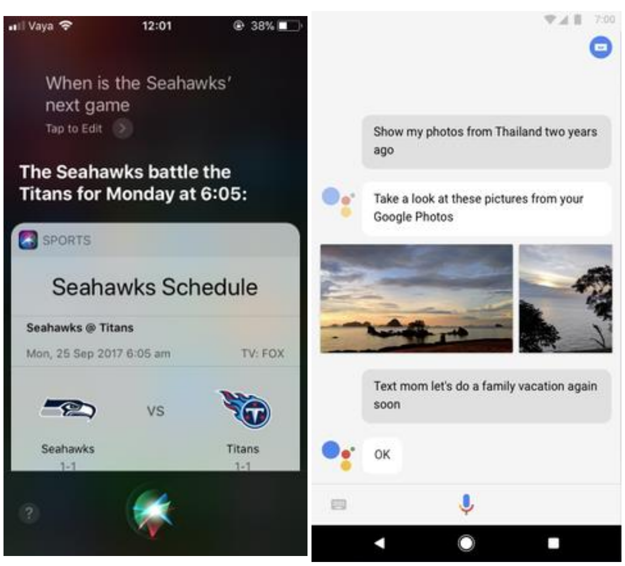
Search Engines

Machine learning is used in search engines to parse queries and determine their intent. Another set of ML algorithms is then used to retrieve the information relevant to a query before outputting that information as part of the search results.



Personal Assistants

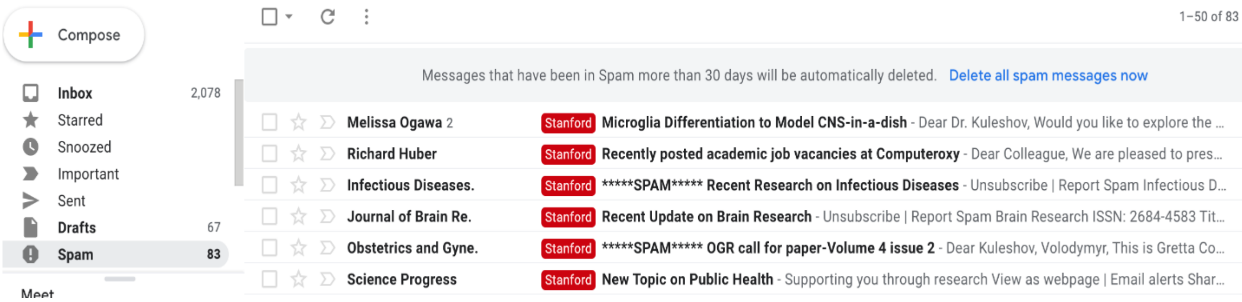
Smartphones with personal assistants like Apple Siri or Google Assistant also rely heavily on machine learning.



The assistant software uses speech recognition algorithms powered by ML to transform the sound of your voice into a sequence of characters or words. It then uses a different set of ML algorithms to infer the intent of your command as well as to perform the processing needed to compute the correct response (in the above example, finding images from Thailand).

Spam and Fraud Detection

Machine learning helps keep your inbox clean and spam-free. Email software uses classification algorithms to identify spam and non-spam email.



More generally, financial companies rely on ML to flag potentially fradulent transaction. Machine learning is one reason for why your credit card account is relatively safe from fraud!

Autonomous Vehicles

Our final example is farther out in the future than the others. Most autonomous vehicles under development today rely on various forms of machine learning to detect objects on the road, read signs, and to plan their movements.

When widely deployed, autonomous vehicles have the potential to transform transportation by reducing its cost and giving access to personal mobility to persons who would otherwise not be able to operate a vehicle (e.g., the blind).

1.1.2. Definition of Machine Learning

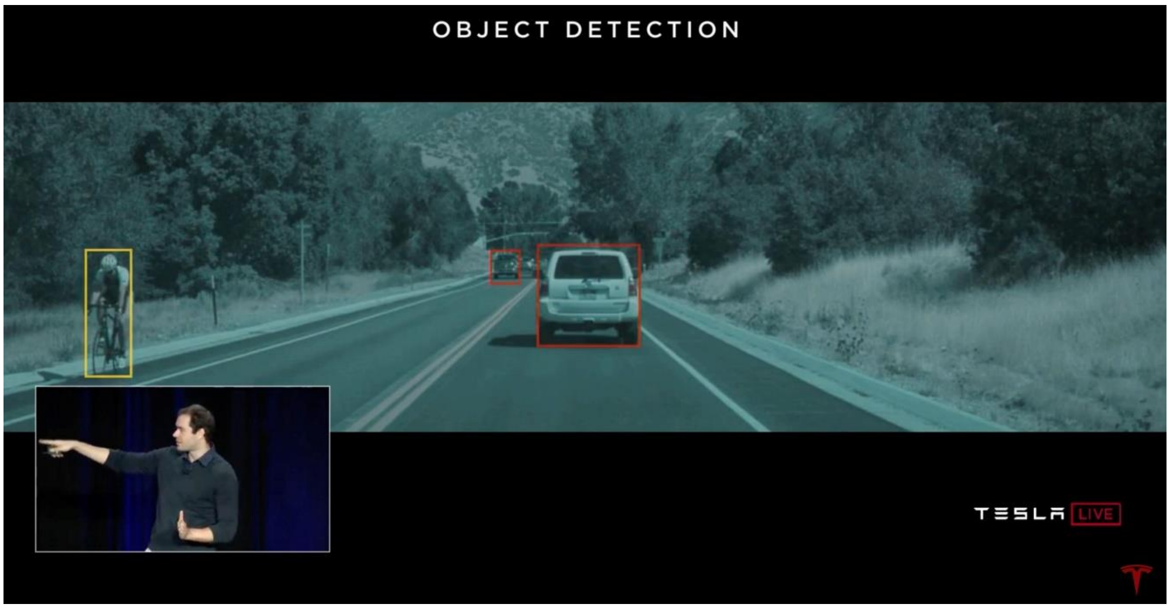
We have seen a few examples of what machine learning is. Let’s now try to define it formally. We will start with the following definition, first proposed by the Arthur Samuel in 1959.

Machine learning is a field of study that gives computers the ability to learn without being explicitly programmed.

This definition is used in numerous courses and textbooks. At first, it might be hard to grasp what Samuel means by terms like "learn" and "explicitly programmed". Let's look at one final example to clarify this.

Self-Driving Cars: A Rules-Based System

We return to our previous example: autonomous vehicles. A self-driving car uses dozens of components based on machine learning. One such component is object detection: given input from the car's sensors, we want to automatically identify cars, cyclists, pedestrians, and other objects on the road.



How might we build an object detection systems for a car? The classical programming approach is to write down a set of rules.

For example, if we see an object, and it has two wheels, then it is likely to be a bicycle. We can incorporate this logic as one of the rules implemented by our system.

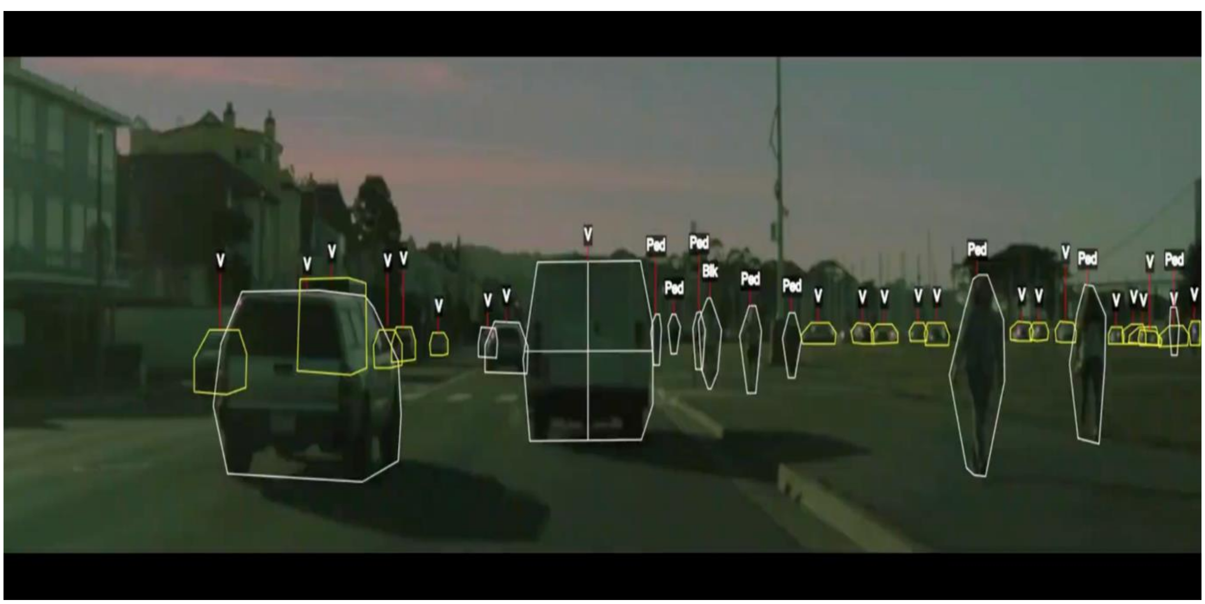
However, in the above image, some cars are seen by the camera from the back. In such cases, cars also appear to have two wheels! In a rules-based system, we need to write an exception to our earlier rule to handle objects seen from the back. Below is pseudocode that tries to implement this idea.

```
# pseudocode example for a rule-based classification system
object = camera.get_object() # assumes we have a "camera" API
if object.has_wheels(): # does the object have wheels?
    if len(object.wheels) == 4: return "Car" # four wheels => car
    elif len(object.wheels) == 2:,
        if object.seen_from_back():
            return "Car" # viewed from back, car has 2 wheels
        else:
            return "Bicycle" # normally, 2 wheels => bicycle
return "Unknown" # no wheels? we don't know what it is
```

You can probably see that this approach doesn't scale. Even in this very simple example, we have run into edge cases that simple rules cannot handle. Imagine now how many edge cases we would encounter if we tried to build a rules-based system for all the possible environments that a self-driving car might encounter. Clearly, it is almost impossible for a human to specify rules for all the scenarios that can arise in autonomous driving. The rules-based solution does not scale.

Self Driving Cars: An ML-Based System

Machine learning is an alternative approach to building software systems that instead tries to *teach* a computer how to perform tasks by providing it examples of desired behavior. In this example, we might collect a large dataset of labeled objects on the road. We then feed this dataset to a short meta-algorithm through which the computer automatically learns what a cyclist or a car look like. It then uses this knowledge to detect new objects on the road.



This approach is much more scalable: we no longer need to directly specify the correct behavior for every possible image frame—the computer learns the desired behavior from data.

Revisiting Our Definition of ML

This example should now help us better understand the definition proposed by Arthur Samuel. Machine learning is a way of building software systems without explicitly programming their behavior: instead computers can learn to perform the desired behavior on their own from a small number of examples. This principle can be applied to countless domains: medical diagnosis, factory automation, machine translation, and many others.

1.1.3. Why Machine Learning?

We end this part of the lecture with some final thoughts on the reasons on why you should study machine learning.

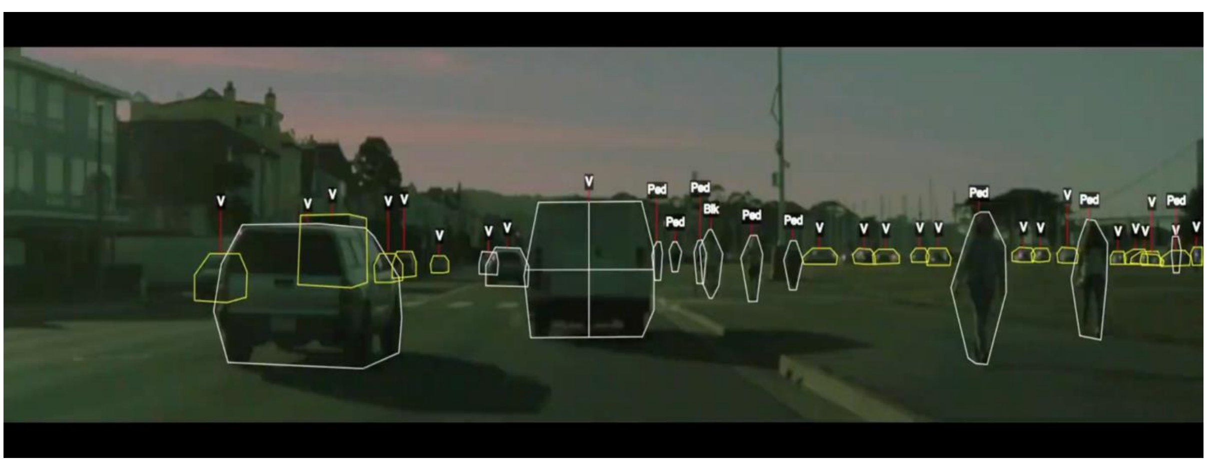
- First, machine learning is the only way of building certain kinds of software. Object detection is one example, but machine learning also produces the best performing systems for a wide range of tasks such as machine translation, speech recognition, image classification, and many others.
- Learning is also widely regarded as a key approach towards building general-purpose artificial intelligence. By developing learning algorithms, we create techniques that may one day enable us to create true AI.
- Lastly, machine learning can offer insights into human intelligence. By studying artificial systems, we can also make discoveries about the human mind.

1.2. Two Approaches to Machine Learning

It is common to define three broad subfields of machine learning which implement three different approaches for creating learning algorithms.

1.2.1. Supervised Learning

The most common type of machine learning is supervised learning. Most of our previous examples have been instances of this approach.



Supervised learning implements the following strategy:

1. First, we collect a dataset of labeled training examples.
2. We teach a model to output accurate predictions on this dataset.

3. When the model sees new, similar data, it will also be accurate.

In addition to many examples introduced earlier, supervised learning is widely used for tasks such as:

- **Classifying medical images**. Given a large datasets of images of malignant and benign tumors, we seek to develop a system that can identify tumors in new images.
- **Translating between pairs of languages**. Here, supervision comes in the form of pairs of sentences that have the same meaning in two different languages.
- **Detecting objects in a self-driving car**. We provide the model with examples of cars, pedestrians, etc.

Pros of Supervised Machine Learning

- You will have an exact idea about the classes in the training data.
- Supervised learning is a simple process for you to understand. In the case of unsupervised learning, we don't easily understand what is happening inside the machine, how it is learning, etc.
- You can find out exactly how many classes are there before giving the data for training.
- It is possible for you to be very specific about the definition of the classes, that is, you can train the classifier in a way which has a perfect decision boundary to distinguish different classes accurately.
- After the entire training is completed, you don't necessarily need to keep the training data in your memory. Instead, you can keep the decision boundary as a mathematical formula.
- Supervised learning can be very helpful in classification problems.
- Another typical task of supervised machine learning is to predict a numerical target value from some given data and labels.

Cons of Supervised Machine Learning

- Supervised learning is limited in a variety of sense so that it can't handle some of the complex tasks in machine learning.
- Supervised learning cannot give you unknown information from the training data like unsupervised learning do.
- It cannot cluster or classify data by discovering its features on its own, unlike unsupervised learning.
- In the case of classification, if we give an input that is not from any of the classes in the training data, then the output may be a wrong class label. For example, let's say you trained an image classifier with cats and dogs data. Then if you give the image of a giraffe, the output may be either cat or dog, which is not correct.
- Similarly, let's say your training set does not include some examples that you want to have in a class. Then, when you use those examples after training, you might not get the correct class label as the output.

- While you are training the classifier, you need to select a lot of good examples from each class. Otherwise, the accuracy of your model will be very less. This is difficult when you deal with a large amount of training data.
- Usually, training needs a lot of computation time, so do the classification, especially if the data set is very large. This will test your machine’s efficiency and your patience as well.
- We can not always give lots of information with supervision. A lot of the time, the machine needs to learn by itself from the training data. As Geoffrey Hinton quoted in 1996, *“there’s only one place you can get so much information, that is, from the input itself* “

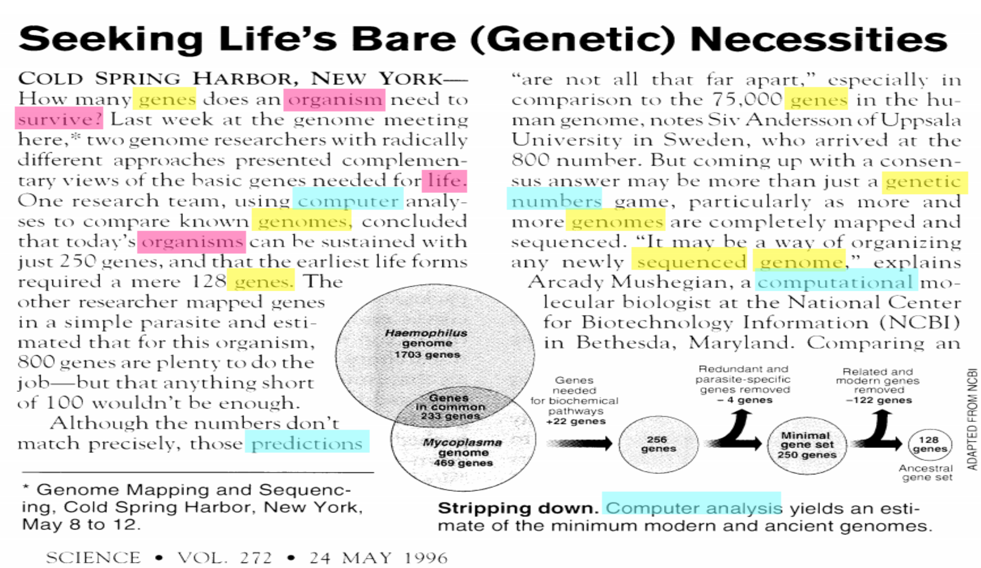
1.2.2. Unsupervised Learning

In unsupervised learning, we start with a dataset *that does not contain any labels*. Unsupervised learning seeks to discover interesting and useful patterns in this data, such as:

- **Clusters of related datapoints**. For example, we might want to discover groups of similar customers from the logs of an e-commerce website.
- **Outliers**, i.e., particularly unusual or interesting datapoints. For example, suspicious financial transacations.
- **Denoised signals**. Recovering an image corrupted with white noise.

An Example of Unsupervised Learning

Let’s look more closely at one common real-world application of unsupervised learning. Consider the following text, which contains at least four distinct topics.



Seeking Life’s Bare (Genetic) Necessities

COLD SPRING HARBOR, NEW YORK—How many genes does an organism need to survive? Last week at the genome meeting here,* two genome researchers with radically different approaches presented complementary views of the basic genes needed for life. One research team, using computer analyses to compare known genomes, concluded that today’s organisms can be sustained with just 250 genes, and that the earliest life forms required a mere 128 genes. The other researcher mapped genes in a simple parasite and estimated that for this organism, 800 genes are plenty to do the job—but that anything short of 100 wouldn’t be enough.

Although the numbers don’t match precisely, those predictions “are not all that far apart,” especially in comparison to the 75,000 genes in the human genome, notes Siv Andersson of Uppsala University in Sweden, who arrived at the 800 number. But coming up with a consensus answer may be more than just a genetic numbers game, particularly as more and more genomes are completely mapped and sequenced. “It may be a way of organizing any newly sequenced genome,” explains Arcady Mushegian, a computational molecular biologist at the National Center for Biotechnology Information (NCBI) in Bethesda, Maryland. Comparing an

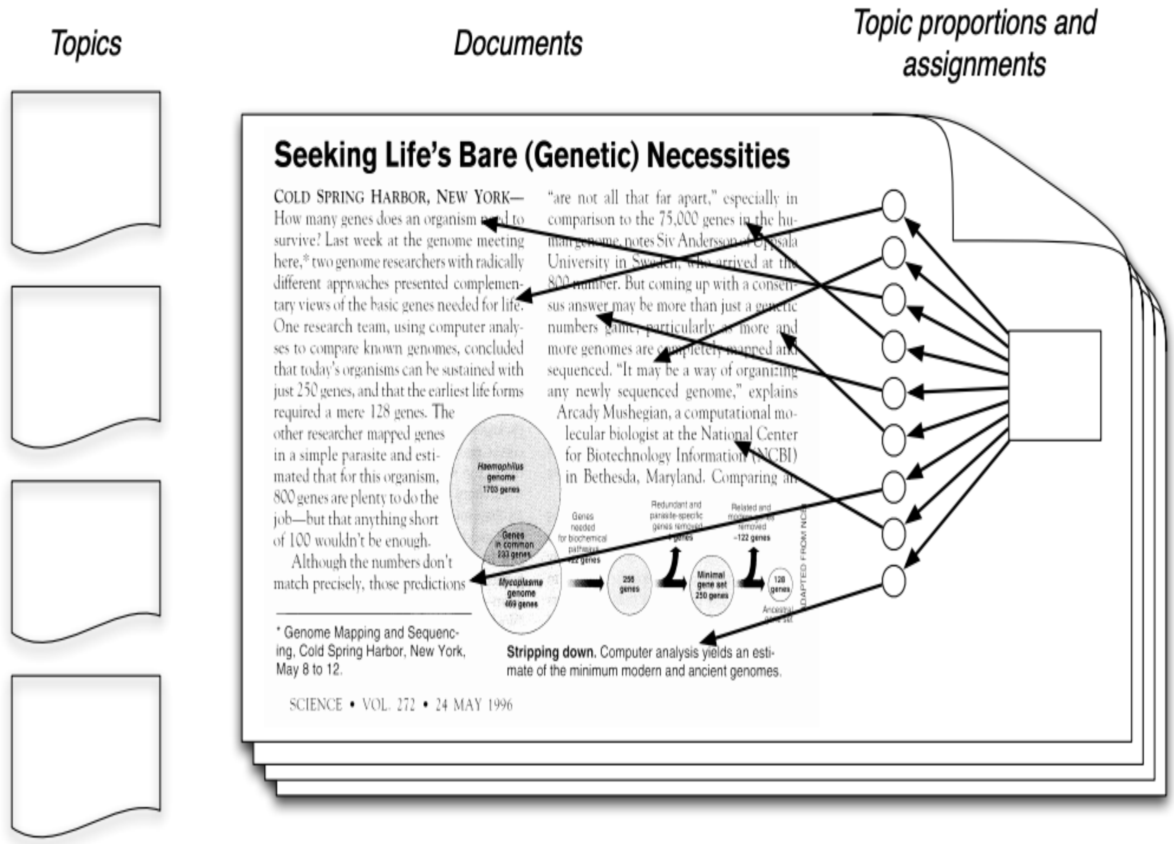
Stripping down. Computer analysis yields an estimate of the minimum modern and ancient genomes.

* Genome Mapping and Sequencing, Cold Spring Harbor, New York, May 8 to 12.

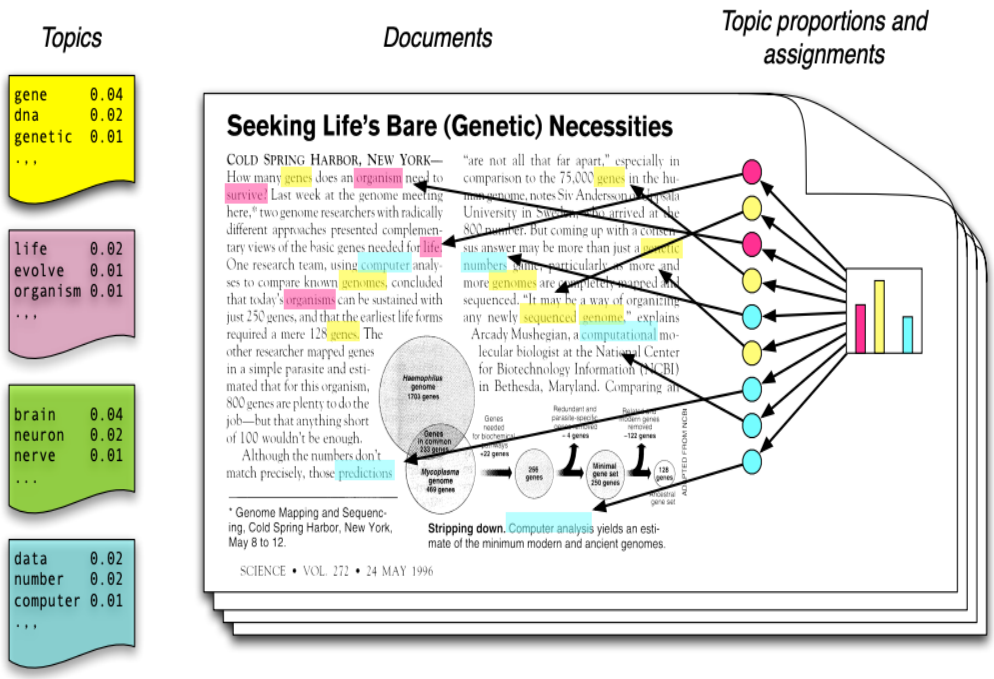
SCIENCE • VOL. 272 • 24 MAY 1996

The blue words pertain mostly to computers. The red words pertain to biology. The yellow words are related to genetics.

It would be useful to be able to detect these topics automatically. However, in practice we rarely have access to text in which each word is labeled with a topic.



Unsupervised topic models automatically discover clusters of related words (these are the "topics", e.g., computers) and assign a topic to each word, as well as a set of topic proportions to each document.



This kind of analysis can be useful for automating research in the social sciences, as well as for accelerating the analysis of financial documents. One of the most well-known topic modeling methods is called latent Dirichlet allocation.

Other Applications of Unsupervised Learning

Unsupervised learning has numerous other applications:

- **Recommendation systems**. For example, the recommendation engine at Netflix is based on the unsupervised discovery of common viewing patterns across users.
- **Anomaly detection**. The field of predictive maintenantce seeks to identify factory components that are likely to fail soon.
- **Signal denoising**. Extracting human speech from a noisy audio recording.

Pros of Unsupervised Learning

- It can see what human minds cannot visualize.
- It is used to dig hidden patterns which hold utmost importance in the industry and has widespread applications in real-time.
- The outcome of an unsupervised task can yield an entirely new business vertical or venture.
- There is lesser complexity compared to the supervised learning task. Here, no one is required to interpret the associated labels and hence it holds lesser complexities.
- It is reasonably easier to obtain unlabeled data.

Cons Of Unsupervised Learning

A few of the disadvantages of unsupervised learning are:

- It is costlier as it might require human intervention to understand the patterns and correlate them with the domain knowledge.
- It is not always certain that the obtained results will be useful since there is no label or output measure to confirm its usefulness.
- One cannot accurately define the sorting and output of an unsupervised task. It is heavily dependent on the model and in-turn on the machine.
- The results often have lesser accuracy.